Ocean surface current retrieval using a non homogeneous Markov-switching multi-regime model

Pierre Tandeo, Ronan Fablet, Pierre Ailliot

OCEAN SURFACE CURRENT RETRIEVAL USING A NON HOMOGENEOUS MARKOV-SWITCHING MULTI-REGIME MODEL

Pierre Tandeo, Ronan Fablet[*]

Telecom Bretagne
Department Signal & Communications
Technopôle Brest-Iroise, France

Pierre Ailliot

University of Brest
Mathematical laboratory
Brest, France

ABSTRACT

This paper addresses the reconstruction of sea surface currents from satellite ocean sensing data. Whereas the classical surface currents derived from the SSH (Sea Surface Height) products are rather low space-time resolution fields (typically, 50 km and 12-day actual space-time grid resolution), we investigate the extent to which we can retrieve sea surface currents at higher resolution using daily SST (Sea Surface Temperature) satellite observations. State-of-the-art methods, which exploit classical optical flow schemes or nonlinear regression techniques, do not provide satisfactory results due to the space-time variabilities of the relationships between the SST and the sea surface current. Motivated by our recent joint SST-SSH identification of characterization of upper ocean dynamical modes, we here show that a multi-regime model, formally stated as a Markov-switching latent class regression model, provides a relevant model to capture the above-mentioned variabilities and reconstruct SST-driven sea surface currents. The considered case study within the Agulhas current demonstrates that our model retrieves high-resolution space-time details which cannot be resolved by the classical SSH-derived products.

Index Terms— Sea surface temperature, Sea surface current, Ocean surface dynamics, Latent class regression, Non homogeneous Hidden Markov model

1. INTRODUCTION

Satellite altimeter sensors have low revisit rates (about 12 days) and provide very sparse measurements of zonal and meridional ocean surface currents (U,V) derived from the Sea Surface Height (SSH). Overall, SSH products (e.g., Aviso) typically reaches spatial resolutions of about 50 km and time resolutions from 7 to 12 days (cf. [1]). By contrast, satellite microwave and infrared sensors provide Sea Surface Temperature (SST) with much higher spatial and temporal resolutions (up to 5 km spatially and daily temporally, see e.g., [2] and [3]).

Depending on the underlying upper ocean dynamics, SST is an active/passive tracer of these dynamics. Hence, joint SST-SSH analysis has a clear potential to increase the space-time resolution of satellite-derived sea surface currents. Though a number of studies have investigated this potential, it remains to our knowledge an open issue, especially due to the space-time variabilities of the SST-SSH relationships.

Among the related previous work, one may cite optical flow methods using space-time differential operators applied to SST fields (see e.g. [4], [5], [6]), fluid mechanics models as in the Surface Quasi-Geostrophic (SQG) theory (cf. [7], [8], [9], [10], [11]) or statistical approaches learning relationships between satellite surface currents and local SST variations using nonlinear model (cf. [12]) or introducing a latent variable (cf. [13]). In [13], we investigated the decomposition of the relationship between SST and SSH fields and showed that only a few dynamical modes, characterized by linear and local SST-SSH transfer functions, may be considered to characterize the space-time variabilities of upper ocean dynamics within an active ocean region (namely, a region embedding the Agulhas current). In this work, we further explore such latent class models, beyond the characterization of the upper ocean dynamics, for the reconstruction of daily sea surface currents from a joint SST-SSH analysis. To this end, we extend the latent class model introduced in [13] to a space-time Markov-switching model and state the reconstruction of the daily sea surface currents as a Bayesian assimilation issue. Then, we evaluate the proposed model qualitatively with respect to the reference Aviso product.

This paper is organized as follows. Section 2 presents the proposed Markov-switching latent model, including model calibration and assimilation issues, with a view to reconstructing daily sea surface currents from a joint SST-SSH data analysis. In Section 3, the application to real satellite observations is reported. We further discuss and summarize the key results of this study in Section 4.

[*]Thanks to Aviso and RSS projects for providing data.

2. METHODS

2.1. Remote sensing data

Hereafter, as SST and SSH data, we use respectively the RSS[1] and Aviso[2] products. The RSS uses abundant microwave SST measurements whereas the Aviso product is a spatio-temporal interpolation of very sparse altimeter along-track data. In this study, we interpolate the two products on the same daily $1/4°$ grid. We focus on the Agulhas region during the year 2004 since four altimeters were available (see [1] for more details). According to the spatial resolutions of the RSS and Aviso products, we study the mesoscale structures, from 50 to few hundred kilometers.

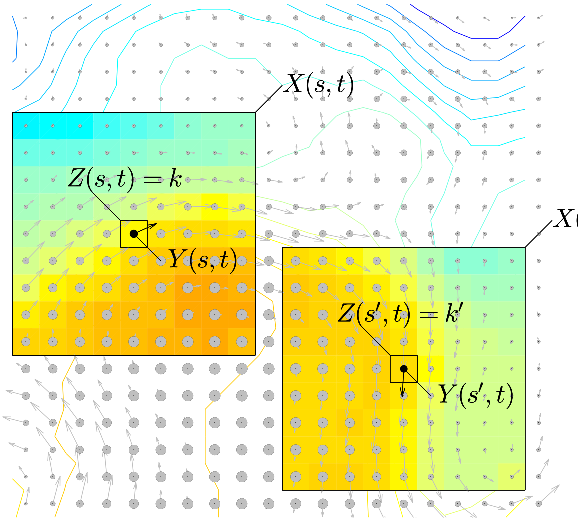

Fig. 1. Sketch of SST patches (9×9 pixels in degree represented in false colours), noted $\mathbf{X}$, and the corresponding SSHs (in meter represented by dots) and surface currents (in meter per second represented by quivers) noted $\mathbf{Y}$ at the central location s and s' at time t. The dynamical mode is noted Z and informs on the k^{th} relationships between $\mathbf{X}$ and $\mathbf{Y}$.

2.2. Multi-regime SST-SSH model

Our model assumes that the local SSH variability locally relates to the SST field in a neighboring region (i.e. 9×9 pixels, cf. Fig. 1). For a given spatio-temporal location (s,t), $\mathbf{Y}(s,t)$ encodes the local SSH variability through a 3-dimensional vector formed by the SSH value and the geostrophic surface current (U,V). $\mathbf{X}(s,t)$ refers to the vectorized version of the local SST patch (p-dimensional vector) centered in s at time t. Assuming that different dynamical modes between SST and SSH may be exhibited, we denote by $Z(s,t)$ the latent variable corresponding to the hidden ocean surface dynamical mode in play at location s and time t. Formally, following our previous work [13], we consider a latent class regression such that the likelihood of $\mathbf{Y}$ conditionally to $\mathbf{X}$ and $Z = k$ is given by

$$p\left(\mathbf{Y}|\mathbf{X}, Z = k\right) \propto \mathcal{N}_k\left(\mathbf{Y}; \mathbf{X}\boldsymbol{\beta}_k, \boldsymbol{\Sigma}_k\right) \tag{1}$$

where $\mathcal{N}_k$ represents a multivariate Gaussian probability density with mean $\mathbf{X}\boldsymbol{\beta}_k$ and covariance $\boldsymbol{\Sigma}_k$. Here, each $\boldsymbol{\beta}_k$ correspond to a spatial convolution operator. The inference of model parameters (i.e. the statistical parameters given in Eq. (1) and the number of modes K) involves classical Bayesian inference techniques (cf. [14]).

2.3. Surface current estimation using Markovian priors

To retrieve daily surface currents fields from the multi-regime model defined by Eq. (1), we need a complete SST information and a relevant inference of the dynamical mode in play at any space-time location. In practice, the microwave SST provided by RSS is available daily, even in cloudy conditions. To obtain the information of the hidden dynamical mode, we use the joint SST-SSH given by the RSS and Aviso products. To overcome the low effective temporal resolution of the Aviso product, we address the inference of the dynamical modes at a daily resolution using non-stationary (location-specific) Markovian priors. The non-stationarity of the priors is motivated by the clearly location-specific temporal variability of the upper ocean dynamics (e.g., the spatially stable main Agulhas current involves state transitions different from zones near spatially varying SST fronts). Besides, SST patch descriptors may also help in the the recognition of the local dynamical mode in play, which motivates the introduction of non homogeneous (i.e., local SST-driven) transition priors. In this work, we consider as SST patch descriptor the mean SST, denoted by $\overline{\mathbf{X}}(s,t)$, as it was experimentally shown to be a potentially discriminant feature for the different dynamical modes. Overall, the Markovian priors $P(Z(s,t)|Z(s,t-1), \overline{\mathbf{X}}(s,t))$ follow the graphical representation reported in Fig. 2.

$$\begin{array}{ccccccc} & & & & \{\mathbf{X}(s,t), \mathbf{Y}(s,t)\} & & \\ & & & & \uparrow & & \\ \cdots & \rightarrow & Z(s,t-1) & \rightarrow & Z(s,t) & \rightarrow & \cdots \\ & & & & \uparrow & & \\ & & & & \overline{\mathbf{X}}(s,t) & & \end{array}$$

Fig. 2. Directed acyclic graph of the proposed model. At a specific location s, we use a non homogeneous hidden Markov chain to model the temporal evolution of the dynamical mode Z. The delay between two consecutive times is one day.

[1] Remote Sensing System, available online at *http://www.ssmi.com/*
[2] available online at *http://www.aviso.oceanobs.com/*

We infer the parameters of these Markovian priors using the Expectation-Maximization procedure (cf. [15]). Given the inference of model parameters (i.e., multi-regime SST-SSH model in Eq. (1) and Markovian priors as schematized in Fig. 2), the SST-driven reconstruction of the sea surface currents involves two steps. We first compute the posterior likelihoods of the hidden dynamical modes from a classical forward-backward algorithm (cf. [16]). Second, at each location s and time t, we apply Eq. (1) to estimate the sea surface currents at a daily resolution using the weighted regression

$$\hat{\mathbf{Y}}(s,t) = \sum_{k=1}^{K} P\left(Z(s,t)=k|Z(s,t-1), \overline{\mathbf{X}}(s,t)\right) \times \mathbf{X}(s,t)\hat{\boldsymbol{\beta}}_k. \quad (2)$$

3. RESULTS

3.1. Statistical parameter estimation

We follow the same procedure as in [13] for the calibration of the multi-regime SST-SSH model given in Eq. (1). In the Agulhas region, we resort to $K = 4$ hidden dynamical modes, corresponding to 4 different slopes and covariances in the regression between the local SST ($\mathbf{X}$) and the local SSH ($\mathbf{Y}$). We also show that the dynamical modes correspond to geostrophic or advective displacements with different amplitudes (see [13] for more details).

Then, we perform the inference of the stationary laws and non homogeneous (i.e., time varying) transition matrices of the HMM given in Fig. 2. The results (not shown here) indicate very large differences between locations, especially for the temporal transitions between the different dynamical modes. We also denote an impact of the non homogeneous part of the model, i.e. the intra-patch SST mean.

3.2. Surface current retrieval

Here, we focus on the Agulhas return current region, between longitudes $30°$E to $42°$E and latitudes $36°$S to $44°$S during the year 2004. This active ocean region involves important space-time variabilities of the sea surface currents, which makes it particularly relevant for our study. Moreover, as reported in [17] in this same zone, classical linear and nonlinear models provide very poor results compared to the multi-regime model proposed here.

As schematized in Fig. 3, we use daily maps of SST (first column) and SSH (second column) respectively provided by the RSS and Aviso products. Then, following the non homogeneous HMM presented in Fig. 2, we compute the daily and smoothed *a posteriori* probabilities corresponding to the $K = 4$ dynamical modes (third column, black corresponding to high probability). Finally, applying our fuzzy regression given in Eq. (2), we obtain SST-driven sea surface currents (fourth column). In this same column, in order to facilitate the comparisons, we also indicate the contour plot of the SSH provided by Aviso. The first three rows correspond to a 2-weeks situation in January 2004. It involves a large eddy (top-left of the image), during its merging with the strong return Agulhas current (middle part of the image). The 15^{th} of January, analyzing the SST image and the estimated surface currents, we can see that the eddy has been absorbed. At the contrary, due to a strong spatio-temporal interpolation, the Aviso results are very weak and are not able to see this absorption. Another 2-weeks situation, in July 2004, is reported in the last three rows. In this case, the SST corrects the centers and the shapes of the cyclonic and anticyclonic eddies at the top of the image, especially the 4^{th} of July. It confirms the results of [18] where they conclude that the microwave SST can be use to correct the phase of the Aviso products.

4. CONCLUSION

In this paper, we use a multi-regime model to predict surface geostrophic currents from single snapshots of thermal information. We learn the temporal transitions between the different regimes (here corresponding to different dynamical modes at the surface of the ocean) using Markovian priors. We test the methodology on the strong return Agulhas current. The results clearly stress the relevance of our approach. For instance, the use of SST images help us to track the evolution of fronts or large eddies not always seen by the altimeters.

In future works, we plan to extend the number of dynamical modes (here, only four) to produce better estimations of surface currents. We also plan to use additional remote sensing data of sea surface salinity and ocean coulour or *in situ* measurements of the Mixed Layer Depth (MLD) as non homogeneous part of our HMM.

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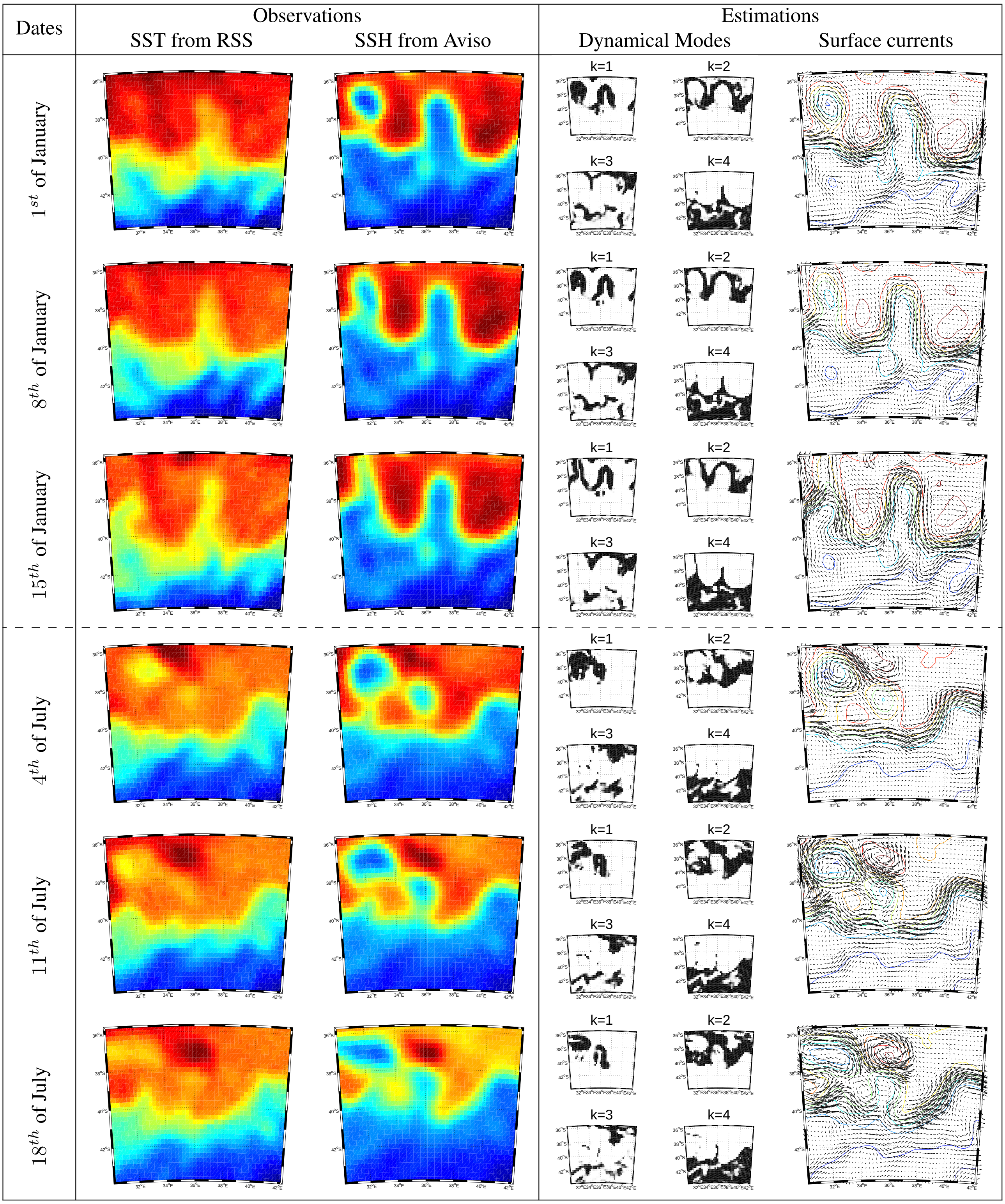

Fig. 3. Satellite SST (first column) and SSH (second column) products provided by the RSS and Aviso projects. Posterior probabilities for each dynamical mode (third column, black as high probability). Surface current estimates using SST and posterior probabilities, along with the contour plot of the SSH provided by Aviso (fourth column).

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